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Humans do not always act selfishly: social identity and helping in emergency evacuation simulation

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Abstract

To monitor and predict the behaviour of a crowd, it is imperative that the technology used is based on an accurate understanding of crowd psychology. However, most simulations of evacuation scenarios rely on outdated assumptions about the way people behave or only consider the locomotion of pedestrian movement. We present a social model for pedestrian simulation based on self-categorisation processes during an emergency evacuation. We demonstrate the impact of this new model on the behaviour of pedestrians and on evacuation times. In addition to the Optimal Steps Model for locomotion, we add a realistic social model of collective behaviour.

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1. Introduction

An abundance of research has been conducted on pedestrian dynamics for safety and event planning of crowds, including simulations of pedestrian evacuation during fires (Ran et al. (2014); Wagner and Agrawal (2014)), the movement of pedestrians through buildings (Kamkarian and Hexmoor (2013); Sagun et al. (2011)), simulations of realistic pedestrian movement (Chraïbi et al. (2010); Moussaïd et al. (2011); Seitz and Köster (2012); Davidich and Köster (2013)), and the monitoring of pedestrian flow at public events (Zhang et al. (2013)). Although this work is crucial for safety management and organisation, a recent systematic review by Templeton et al. (in preparation) found that previous simulations of crowd behaviour have treated crowds as either mindless masses – wherein the crowd is merely an unthinking mass of numerous individuals with no connection to one another – or as consisting of smaller groups within a crowd. Specifically, it was found that some modellers are basing these approaches on outdated theories of crowd psychology which have been recently superseded in the social science literature by accounts which can explain mass behavior without positing mindlessness. For example, in some simulations of emergency crowd

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behaviour, crowd members act as individuals with no group affiliation (Yan et al. (2012); Shao et al. (2013)), or merely panic (Helbing et al. (2000); Franca et al. (2009)). Further, models that suggest that small groups of affiliates stick together in emergencies (e.g. Shao et al. (2013); Zheng et al. (2014)) are correct for crowds in which there are groups of families and friends (Sime (1980)). However, they do not apply to those crowds where people are amongst strangers and yet still behave socially (e.g. crowds of commuters). As yet, no model of crowd behaviour has been developed which has sufficiently accounted for large scale collective crowd behaviour where strangers in a crowd act together in a spontaneous and yet coordinated way.

There are numerous examples of crowds acting together in a coordinated manner, for example in urban riots (Reicher (1984)), religious mass gatherings (Alnabulsi and Drury (2014)), and music festivals (Neville and Reicher (2011)). Crucially, research has also found numerous instances of crowd members coordinating in emergency situations (Drury et al. (2009a)). For example, Drury et al. (2009a) analysed accounts of survivors from numerous disasters, such as fires, crushings in football stadiums, and the sinking of two cruise ships. In the accounts, rather than the irrational panic or small group behaviour that has been suggested in previous simulations of crowd behaviour, survivors often described people forming orderly queues, acting calmly despite the emergency situation, and gave descriptions of “camaraderie” and “pulling together as opposed to pulling apart” (p. 495).

Over recent years an increasing number of crowd modellers have acknowledged that the inclusion of theory and research from contemporary crowd psychology is necessary in order to create an adequate simulation of crowd behaviour (for examples, see Langston et al. (2006); Smith et al. (2009); Aguirre et al. (2011); Köster et al. (2011)). However, as yet, most of these examples have modelled small group phenomena, and no model has simulated collective behaviour across an entire crowd without falling back into the mindless mass approach. In order to develop a more realistic simulation of crowd behaviour where a crowd can act as one cohesive unit, modellers can benefit from incorporating the most up to date research findings of psychologists on collective behaviour. One prominent theory of crowd behaviour which is grounded in empirical research and can explain a range of collective behaviour is self-categorisation theory (Turner (1985); Turner et al. (1987)), which is part of the social identity approach (Tajfel and Turner (1979)).

2. The social identity approach and self-categorisation theory

The social identity approach originated to foreground the social world as an explanation for human behaviour, focusing on how social structures impact upon cognition. According to the social identity approach, as well as personal identities, we each have numerous social identities, based on social categories and groups. We act in accordance with the social identity that is salient at a particular time (Tajfel and Turner (1979); Turner et al. (1987)). Self-categorisation theory is that part of the social identity approach that accounts for people’s perception of their own group membership and the group membership of others. The theory suggests that it is this categorisation of group membership which makes collective behaviour possible, including how people can come together psychologically within a crowd regardless of prior interpersonal relationships or interactions. Through this process, the individual shifts from their personal identity to their social identity, where their commonality with others becomes salient (Turner et al. (1987)). Through a process of self-stereotyping, individuals conform to the features of the group. Since these features are shared, this explains how people can spontaneously act as one. Thus, it is this process which opens up the possibility for a crowd of strangers to come together as a group.

2.1. *Collective behaviour and collective self-organising in emergency evacuations*

Self-categorisation theory has been shown to explain behaviour in emergency situations, as well as other collective phenomena such as crowd conflict (Reicher (2001)) and mutual support among group members (Haslam et al. (2005)). For example, by using a virtual reality paradigm, Drury et al. (2009c) placed participants in a scenario where they had to escape from a burning underground rail station. It was found that the more that the participants identified as being part of the crowd, the more helping behaviour they exhibited to others and the less likely they were to push them aside in their attempt to escape. The common finding that crowds can come together and help one another in an emergency has implications for how computer modellers should be approaching crowd behaviour. Indeed, Drury et al. (2009a) argue that the crowd should stop being seen as an inherent problem; adaptive behaviour by crowd members as crowd members can actually enhance collective changes of survival and therefore should be conceptualised as a

form of collective resilience. This is evident not only in the finding that people often help one another, but also in the spontaneous coordination and collective self-regulation that occurs in evacuating crowds. In the World Trade Center evacuation, where individuals acted selfishly and caused jams, for example by using their phones and hindering the flow of the rest of the crowd, the other crowd members admonished them, enabling the evacuation to proceed (Drury (2014)). Social psychologists argue that this self-organising and working together that is found among strangers in emergencies is explicable in terms of shared social identity. One example of crowd members self-organising and helping one another based upon a shared group identity, which has been researched by crowd psychologists, is the July 7th London bombings.

2.2. *The event: The July 7th London Bombings*

On July 7th, 2005, four coordinated suicide bomb attacks took place in central London. Three bombs were detonated in carriages of tube trains in the London underground, and another in a double decker bus. The three bombs in the underground were set off at 8.50am within 30 seconds of each other, and the fourth on the bus was set off at 9.47am. As such, the bombings took place during rush hour traffic when the carriages were been particularly full. There were over 700 people injured in the attacks, and 52 people were killed. Survivors feared that there might be other explosions. They were plunged into darkness and the emergency services did not reach them for some time. It was therefore down to the survivors themselves to tend to the injured and to evacuate.

Research conducted by Drury et al. (2009b) found that some survivors described a sense of “unity”, feeling “part of a group” (p. 81), and calmly helped one another to escape safely after the bombs had gone off. Further, the survivors described examples of people helping each other and everyday social norms being maintained even in the dangerous environment. One hundred and forty of 141 contemporaneous accounts from survivors described seeing help, and only three described seeing selfish behaviour. A similar pattern was found in first-hand accounts collected later from internet sources and the public enquiry: 42 out of 127 described seeing help and only 11 described seeing selfishness. For example, people reported leaving in an orderly fashion rather than pushing past each other, and gave accounts of people remaining calm and working together to remove the doors, which they could not have done as individuals acting alone. More survivors described the behaviour of the crowd as orderly than as panicking. Importantly, the helping and cooperative behaviours, such as allowing others to go first, emotionally supporting others, and in some cases attempting to treat their wounds, delayed the exit time of those evacuating. Therefore, rather than simply fleeing for the exits, many people stayed behind with those (strangers) in need of support at a personal cost. Therefore, we can say that the cooperative behaviour exhibited in the crowd of survivors of the London bombings was widely shared: it was collective behaviour.

Within the novel situation of the emergency, the commuters came to see themselves as one – they shared the same social identity – through the common fate they experienced in relation to the bomb explosions. This common fate caused peoples identities to change from being separate individuals to perceiving themselves as being in the same group. The helping behaviour and self-organisation that was reported by the survivors can be explained through this shared group identity.

Although there are numerous examples of this collective, organised, helping behaviour in emergency situations (Drury et al. (2009a)), in this paper we will focus on the helping behaviour that was documented from the London bombings. We argue that in order to adequately simulate collective behaviour in emergency and disaster events, modellers can benefit from awareness of the research conducted by social psychology on crowd behaviour. Specifically, modellers could focus on the emergence of a shared group identity and ingroup helping by incorporating aspects of self-categorisation theory in to their simulations. As such, we use the London bombings scenario to propose a realistic model of collective behaviour (SIMA) which combines the comprehensively validated Optimal Steps Model with principles from the well established self-categorisation theory.

3. Social Identity Model Application

In pedestrian simulations, most modellers focus on the locomotion level, that is, how to get from one place to another. However, pedestrian behaviour and motion does not only depend on the locomotion. It is important to include social behaviours which impact the results of the simulation. Hence, we introduce a second level on top of the

locomotion level: the social level (see Fig. 3). This structure allows models on different levels, e.g. OSM or SFM in the locomotion level, Social Identity Model Application and/or group models on the social level, to be exchanged.

The Social Identity Model Application (SIMA) consists of two parts: the Social Identity Detection (self-categorisation) and the Helping Behaviour. A simplified flowchart of the basic model is shown in Fig.3.

3.1. Social Identity Detection

Self-categorisation theory shows that strangers can become united through sharing a social identity when they experience a common fate in an emergency situation. This in turn can lead to helping fellow ingroup members. Hence, the SIMA starts with Social Identity Detection. In the usual evacuation scenario, the common fate for the involved pedestrians arises by definition at the beginning. Notably, not every person who is involved in a disaster will categorise themselves as an ingroup member with the others to the same degree (Drury et al. (2009a)). As such, not every pedestrian in our simulation should share a common social identity. We use a parameter to control the percentage of pedestrians sharing the social identity.

3.2. Helping Behaviour

We proceed on the assumption that only with a shared social identity are people willing to help strangers. As there are many types of helping behaviour in an emergency, we select which helping behaviour to simulate. We model typical helping behaviour – returning to injured pedestrians and helping them evacuate – in accordance with the findings from Drury et al. (2009a,b). However, other kinds of helping can be easily introduced into the model.

At first, pedestrians in the simulation need to be allocated with the attribute of either being injured or not injured so that they can be identified as such by others. An injured pedestrian – we model only badly injured pedestrians – cannot evacuate without the help of others. The free flow speed, that is, the speed at which the person would move on an empty plane, is set to zero. The percentage of injured pedestrians in the simulation is set by a parameter.

Our goal is to find a model of helping behaviour which is able to produce realistic results in our scenario of interest (see Section 5) and is simple enough to ensure effectiveness and maintain control of the parameters. Helping behaviour will only be triggered if the pedestrians share a social identity with the other survivors and are not injured themselves. Helping splits into three phases: the search for injured pedestrians, the approach to an injured pedestrian and the actual assistance to evacuate:

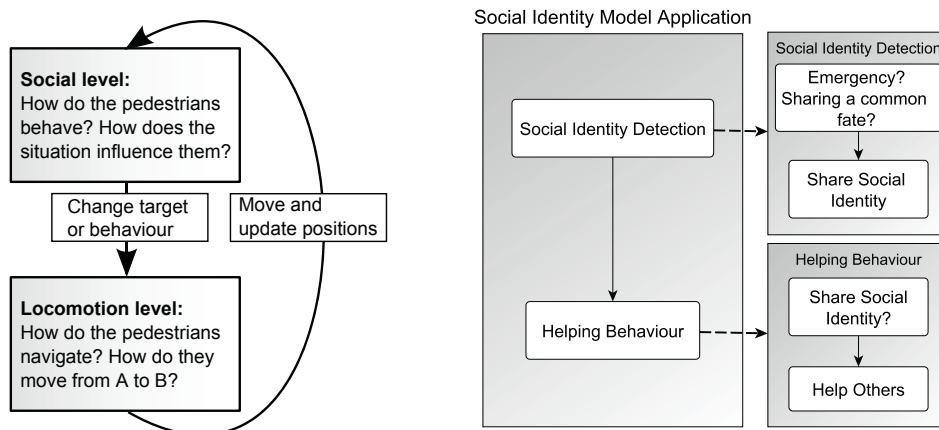


Fig. 1. Possible levels in pedestrian dynamics; the social level on top of the locomotion level. Right: Simplified flow chart of the Social Identity Model Application.] Left: Possible levels in pedestrian dynamics; the social level on top of the locomotion level. Right: Simplified flow chart of the Social Identity Model Application.

- Pedestrians who are not already helping somebody look for unassisted injured persons within their local neighbourhood. The nearest injured pedestrian is chosen as target for the pedestrian on the locomotion level. If no injured pedestrian is found then the pedestrian evacuates individually to the nearest exit.
- When approaching the injured person, potential helpers check continually whether that person is being assisted by somebody else. If so, the potential helper's target is changed to the nearest exit. This avoids multiple helpers.
- Pedestrians who have reached an unhelped injured person form a fixed group with that person. They evacuate with that person through the nearest exit which is set as new common target. The free flow speed for both pedestrians is changed to a slow $0.2 \frac{m}{s}$.

4. Validation of the Social Identity Model Application

A pedestrian model must be extensively validated in order to have significance. Quantitative validation compares the results of the simulation with measurable data. Qualitative validation uses well researched theories of other scientific areas for comparisons. Both should be used to ensure that the results of a simulation model can be trusted. Otherwise, predictions of evacuation times, route choice or pedestrian movement are little better than guesses. The simulation itself becomes little better than a computer game and lacks predictive power.

Quantitative validation is common for the locomotion level and has been thoroughly conducted for the Optimal Steps Model used here (Seitz and Köster (2012); von Sivers (2013); von Sivers and Köster (2014)). For instance, measured density-speed relationships (see Hankin and Wright (1958); Older (1968); Weidmann (1992); Lam et al. (1995)) and evacuation through a bottleneck (Seyfried et al. (2009); Liddle et al. (2011)) can be reproduced.

However, the behaviour in emergencies can change, which prompts the question of how to get data for cases of behaviour in different emergency situations. Unfortunately, there is usually little quantitative data available from emergency situations and it is unclear how to get more, because it would be unethical to perform experiments with real fire, dense crowds or bombs. This is further complicated by the fact that when such disasters do happen, there is often very little camera footage or other observational measurements available. To assess the behaviour of the involved persons, sociologists and psychologists use qualitative and quantitative analysis from interviews with survivors, accounts from newspapers, and witness statements.

Our model, the Social Identity Model Application (SIMA), maps the well researched and validated self-categorisation theory into a computer program. As such, it stays very close to the findings of social psychologists. Also, the behaviour that SIMA introduces in pedestrian evacuation simulation reproduces exactly the same behaviour observed by survivors: people share a social identity and help fellow ingroup members to escape. In this sense, the SIMA is qualitatively validated. Quantitative validation must be postponed until more data is available. Then we will compare our results with the data and calibrate the parameters.

5. Simulation results

We show the results of two scenarios. The first is inspired by the July 7th London bombings where many survivors reported helping behaviour. We demonstrate the new helping behaviour and why this impacts on evacuation times. The second scenario is a fictional evacuation of a building where we compare the evacuation times depending on the amount of injured or helping people.

5.1. July 7th London Bombings

This scenario is inspired by the London Bombings in 2005 described in Section 2.2. A London Underground C69/C77 Circle Line train with six cars is modelled with its real dimensions. The evacuation route, a path along the tracks of the subway, is modelled as a long corridor. In our simulation, every seat is occupied but nobody is standing, resulting in a total of 192 passengers in the train. This setting can be seen in Fig. 5.1 on the left. The explosion of the bomb itself is not modelled. We start the simulation with the evacuation. We assume that 10% of the pedestrians are badly injured and that 80% share a social identity, that is, they are willing to help others. We assume a normally distributed free flow walking speed with mean $1.34 \frac{m}{s}$ and standard deviation of 0.26 but reduce the speed of a helper with charge to $0.2 \frac{m}{s}$.

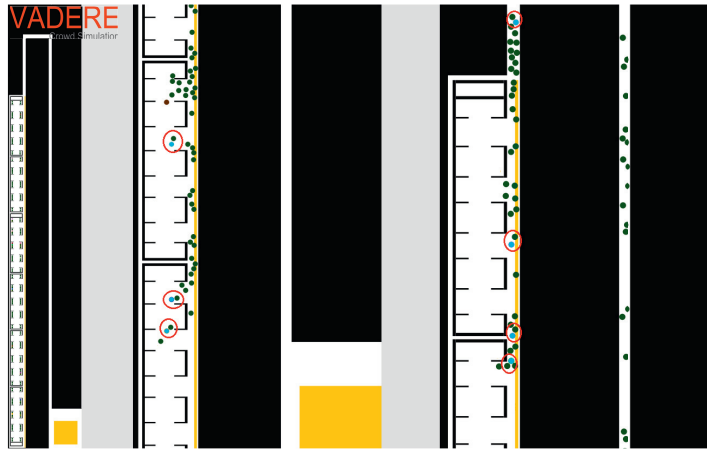


Fig. 2. Screenshots of a tube train evacuation. Left: The whole scenario at the beginning. Every passenger is sitting. The final target is in the lower right corner (yellow). Middle: Screenshot after 20 s of simulation time. Zoom into the two wagons at the back. Evacuating pairs of helper and charge can be observed (marked with a circle around them). Right: Screenshot after 185 s of simulation time. Zoom into the two front wagons. Evacuating pairs of helpers and casualties cause congestion and slow down the evacuation.

Fig. 5.1 shows screenshots during the simulation with pairs of helpers and injured people evacuating together. This is exactly what was reported by survivors and evidenced by photographs taken above ground at the end of the evacuation. In the early state of the evacuation, the injured people are approached by helpers and they become pairs. Those who are neither injured nor assisting others evacuate quickly. Injured people and their helpers need more time which increases the overall evacuation time. Later in the simulation, some of the pairs cause small congestion because they move slower than others and stick together forming an obstacle. Again, this has an impact on the evacuation time. How much the evacuation time changes when more or less people are injured or helping is shown in the next section for a building evacuation.

5.2. Building evacuation

Here, we compare the evacuation time in relation to the number of injured people and those helping others for a fictional building: 70 people are in the building spread over all rooms with fixed starting positions for all simulation runs. Again, we assume a normal distributed free flow speed with mean $1.34 \frac{m}{s}$ and standard deviation of 0.26 for uninjured. This time, the speed of a helper with the injured person is set to $0.4 \frac{m}{s}$. We argue that the floor conditions in buildings are better for walking than in the underground tunnel. The start setting is shown in Fig. 5.2.

The mean evacuation times of 5 simulation runs with 0%, 40%, 60%, and 80% pedestrians sharing a social identity and 0%, 10%, 20%, and 30% injured pedestrians are shown in Table 1. As expected, sharing a social identity without having casualties does not have an effect on the evacuation time within the SIMA. Without having to help injured people, pedestrians evacuate very quickly. However, this is not the case in reality. With badly injured pedestrians but no social identity and thus no helping behaviour associated with it, pedestrians would remain in the building resulting in an infinite evacuation time.

In reality, people often help strangers because of their shared social identity (see Section 2.1). That means, we also need a shared social identity and helping behaviour in our simulation. A simulation with injured, but assisted persons doubles the average evacuation time in this scenario. The more injured people, the more the evacuation time increases. Between the percentages of shared social identity, an interesting effect can be observed: the evacuation time increases with the percentage of persons who share a social identity (between 40% and 60%). If the number of pedestrians who are willing to help increases the average evacuation time increases as well. This can be explained by the greater number of helpers who turn back to provide aid to others. The pedestrians who do not share a social identity and act selfishly cause additional jams at doors because they do not let the helpers pass. This is consistent with observations on the evacuation of the World Trade Center, which suggested that people who acted as individuals

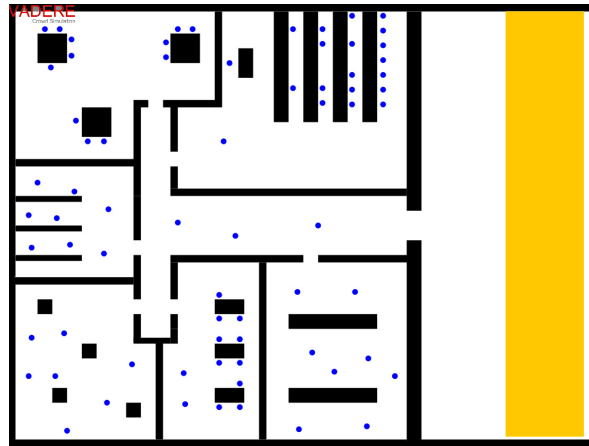


Fig. 3. Evacuation scenario: Evacuation of a fictional building with 70 persons in it. The starting positions of the pedestrians remain the same for all runs. We focus on the evacuation times with different percentages of sharing social identity and of injured persons.

rather than coordinating with the rest of the crowd risked creating jams which could delay the overall evacuation time (Drury (2014)). If the number of pedestrians who share a social identity increases beyond 60% the evacuation time drops again. Now, nearly every injured pedestrian has a helper nearby. Other pedestrians with a shared social identity do not have to turn back and therefore evacuate quickly.

Table 1. Table of averaged evacuation times (in seconds) for a building. The presence of badly injured persons in the absence of any shared social identity and helping behaviour leads to casualties left in the building and infinite evacuation time. The average evacuation time without injured pedestrians in the scenario does not change regardless of whether there are people sharing a social identity or not. Thus, we have one measured reference value in the first line for all columns.

Casualties	People sharing a social identity			
	0%	40%	60%	80%
0 %	48.92	48.92	48.92	48.92
10%	inf	102.56	107.32	102.40
20%	inf	106.60	112.12	107.40
30%	inf	109.12	121.56	117.20

The simulation seems to reflect real behaviour. However, the simulation does not depict the behaviour of coordinated evacuating as mentioned in Baker et al. (2002); Drury et al. (2009b). This is one remaining issue to implement.

6. Conclusion and outlook

In this paper, we presented arguments for the importance of considering the findings of social psychology in pedestrian evacuation dynamics. As a first step we introduced a social model for pedestrian dynamics, the SIMA, which incorporates the social identity approach and specifically self-categorisation theory, the leading theory of crowd psychology, into evacuation simulations. In our results, the impact of shared social identity on evacuation behaviour and evacuation times can be clearly seen. The model is qualitatively validated through its closeness to well established theories from social psychology. Thus we claim that qualitative predictions can be trusted.

Quantitative validation against measured data such as trajectories or evacuation times, on the other hand, remains an open issue. We will attempt to find suitable data which will also allow us to calibrate our parameters. Furthermore, the model will be extended to cover other crucial aspects reported by involved persons in disasters.

A more complex model to cover all the reported behaviour in emergencies is conceivable. Different types of helping could be introduced. In addition, according to Drury et al. (in preparation), the perception of helping behaviour could lead more people to behave the same way (social influence). Finally, for the purposes of our simulation we have assumed that group identification is binary where the survivors were either group members or were not. However,

people also have varying degrees of identification with the group. As such, future research should examine the effect of different levels of group identification upon evacuation time.

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